Leveraging ChatGPT for Efficient Fact-Checking

Emma Hoes[†], Sacha Altay[‡] and Juan Bermeo[§]

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Abstract

We explore the potential of automated online content moderation through Large Language Models (LLMs) as a remedy to the overwhelming surge of online content that fact-checking organizations cannot verify. Although LLMs, such as ChatGPT, may exacerbate this problem by facilitating content production, they could also be leveraged to enhance the efficiency and expediency of fact-checking processes. We conducted a systematic evaluation to measure ChatGPT's fact-checking performance by submitting 21,152 fact-checked statements to ChatGPT as a zero-shot classification. We find that ChatGPT is able to accurately categorize statements as true or false in 69% of cases. Addressing memorization, the performance of ChatGPT is similar on claims that have not been fact-checked or are post its training data cutoff-date. These findings demonstrate the potential of ChatGPT to help label misinformation and deepen our comprehension of how LLMs could improve content moderation practices, complementing the crucial work of human fact-checking experts in upholding the accuracy of information dissemination.

***Keywords*—-** Misinformation, Fact-checking, Artificial Intelligence, AI, Fake News, ChatGPT, LLMs, Content Moderation, PolitiFact

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[†]Postdoctoral Research Fellow, University of Zurich
[‡]Postdoctoral Research Fellow, University of Zurich
[§]Graduate Student, University of Zurich

1 Introduction

There are widespread concerns about the potential adverse impact of Large Language Models (LLMs) like ChatGPT on the quality of our online information ecosystem. ChatGPT can be weaponized to generate false narratives, such as detailed news articles, essays, and social media posts with potentially far-reaching consequences (Newsguard, 2023). There is a particular worry that bad actors, including health fraudsters, authoritarian regimes, and political disinformation campaigners, will leverage this technology as a force multiplier to propagate harmful false narratives globally. At the same time, ChatGPT can produce texts at a speed no human can and offers a bottomless supply of practically free opinion that could crowd out real (human) contributions.

The potential of ChatGPT to crowd out real (human) contributions and exacerbate online misinformation has implications for existing fact-checking efforts to label the veracity of information online, such as PolitiFact and Snopes in the US or FullFact in the UK. Fact-checking remains one of the most prominent and promising ways to counter inauthentic and misleading content (Allen, Arechar, Pennycook, & Rand, 2021; Walter, Cohen, Holbert, & Morag, 2020), which — given the concerns about the negative impact of LLMs on the quality of content — may increase in importance in the years to come. The existence of ChatGPT may, however, not only require fact-checking organizations, or companies such as NewsGuard, to expand or update their criteria to be able to spot sophisticated 'bots' such as ChatGPT, but also to reflect on the realistic scale at which they could produce their ratings. ChatGPT could exponentially increase the amount of (political news) content online, making it even more of an impossible task for fact-checking organizations to label all content. This, on the one hand, could foster what has been called the 'implied truth-effect' (Pennycook, Bear, Collins, & Rand, 2020), which refers to the idea that content that is not labeled or validated in some way or another may be assumed to be true or credible. On the other hand, once bot pundits become indistinguishable from humans, people might start questioning the identity and veracity of everyone and everything online, including otherwise trusted pieces of information. This begs the question of what can be done to prevent these two undesirable scenarios, the one potentially fostering gullibility, and the other skepticism.

We explore the potential of *automated* online content moderation (Hassan et al., 2015; Thorne & Vlachos, 2018) as a potential remedy to the dilemma of an overwhelming surge of online content, where no fact-checking organization, regardless of its scale, can verify all information. Interestingly, although ChatGPT can exacerbate this problem, it can also be leveraged to automatically categorize or fact-check (political) assertions. This is not to say that ChatGPT should or even can replace current endeavors, but rather that it could function as an additional tool for labeling (mis)information. Crucially, this can only be the case if ChatGPT is able to successfully tell facts from fiction. To the best of our knowledge, however, while recent work has explored ChatGPT's potential to rate news outlet credibility (Yang

& Menczer, 2023), no systematic evaluation has been conducted to measure ChatGPT's fact-checking performance.

In this study, we evaluate ChatGPT's performance at classifying verified statements by relying on a database[1] collected from the popular fact-check website *PolitiFact*. The database contains 21,152 statements from 2007 up to including 2022 that have been fact-checked by experts into one of six categories: true, mostly true, half true, mostly false, false and pants on fire, the latter of which is PolitiFact's category for statements that are blatantly false.

Using two different prompts instructing to categorize each of these 21,152 statements into one of the six categories as defined by Politifact (PolitiFact prompt) or as a binary classification into either true or false (binary prompt), we submitted this task to ChatGPT as a zero-shot classification (that is, without additional training). We explore the binary prompt next to the Politifact prompt to extend the generalizability of ChatGPT's performance to other contexts and fact-checking instances which may rely on other systems of classification. A binary true/false system can be used across different languages, cultures, and political systems, as the labels are universally understood. For both prompts, we evaluated the performance of ChatGPT against one primary benchmark, namely its accuracy relative to that of PolitiFact's fact-chekers' verdict. On average across the two prompts, we find that ChatGPT is able to accurately categorize the statements as true or false in 69% of cases, and that the binary prompt is slightly more successful at doing so than Politifact's prompt. We further explore how ChatGPT's performance varies over time (i.e., per year), per source (e.g., news, blog, TV) and per topic (e.g., COVID-19, politics).

Importantly, we also address the issue of memorization[2] by assessing CHatGPT's performance on 1462 true and false claims post its training date (September 2021) using both PolitiFact's and an additional database containing true claims that have not been fact-checked from 2022 [3]. We observe no drop in accuracy. On the contrary, the post-training data lie within the trend we observe by which accuracy increases over time.

The findings of this study demonstrate the potential of leveraging ChatGPT and other LLMs for enhancing the efficiency and expediency of fact-checking processes. By successfully classifying a sizeable corpus of approximately 21,000 statements in a mere 30 hours and at a cost of a modest 10 USD, our research underscores the instrumental role that LLMs can play in automating fact-checking tasks (Demartini, Mizzaro, & Spina, 2020). Indeed, as social media and other digital platforms continue to have an increasingly significant impact on shaping public discourse, it is crucial that we not only deepen our comprehension of how LLMs can be exploited to undermine the integrity of our information

[1] https://www.kaggle.com/datasets/rmisra/PolitiFact-fact-check-dataset

[2] Memorization means that LLMs such as ChatGPT have seen a vast amount of text data during its training process and have memorized the patterns and relationships between words and phrases in that data.

[3] These claims come from Altay, Lyons, and Modirrousta-Galian and a misinformation mega study led by Lisa Fazio, David Rand, Stephan Lewandowsky and Mark Susmann

ecosystem, but also how they could be used to promote conscientious and ethical content moderation practices. However, such technologies should be viewed as a complementary tool, not a replacement, to the crucial work of human fact-checking experts in upholding the integrity and accuracy of information dissemination.

2 Results

For both prompts[4], we relied on a dataset of 21,152 claims that have been rated by fact-checkers from PolitiFact.

First, we prompted ChatGPT to use the same labels as Politifact. After excluding 152 claims on which ChatGPT refused to give a verdict[5] (N = 21'000), we found that 29.96% of the time ChatGPT gave the same verdict as Politifact. This is 13 percentage points above chance assuming that the probability of success by chance is 16.66% across the six verdicts (binomial test: $p < .001$). In Figure 1, on the left panel we offer an overview of ChatGPT verdicts as a function of fact-checkers verdicts. We see that 47% of the mostly-true claims were labeled as mostly-true by ChatGPT, and that 44% of the pants-on-fire claims were labeled as pants-on-fire by ChatGPT. ChatGPT was reluctant to classify any claim as true and thus did poorly on true claims.

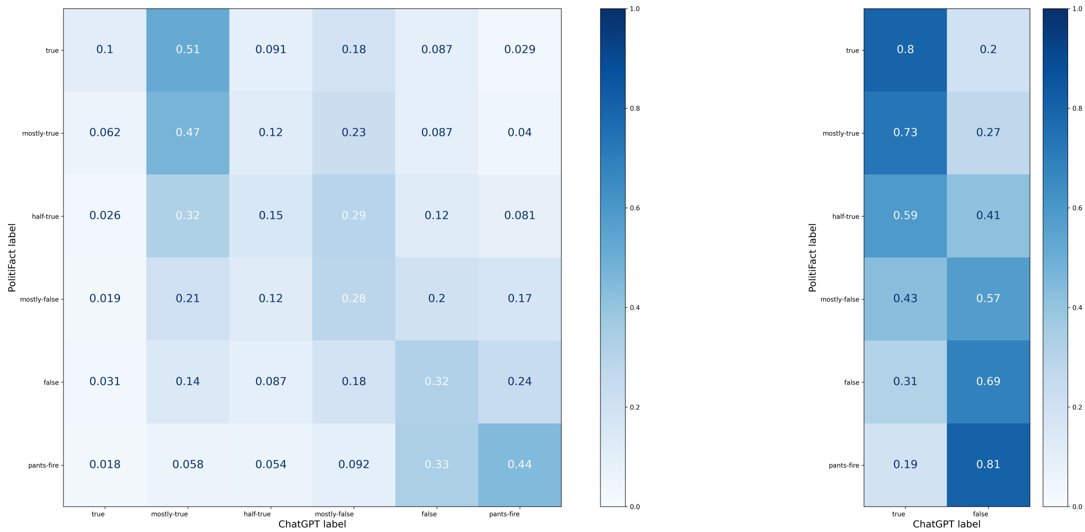

Figure 1: PolitiFact's verdicts vs ChatGPT's verdicts (in percentages wrt. the number of ground truth labels). On the left panel, ChatGPT's verdicts when prompted to use the PolitiFact prompt, as a function of fact-checkers' verdicts (N = 21'000). On the right panel, ChatGPT's verdicts when prompted to use the binary prompt, as a function of fact-checkers' verdicts (N = 19'324)

Next, we investigated alternative ways to estimate accuracy. When merging 'pants-fire' and 'false' into false, 'half-true' and 'mostly-false' into mixed, and 'mostly true' and 'true' into true, we find that

[4]See Section 4.2 for the full prompts
[5]See Section 4.2 for a discussion on this category

ChatGPT accuracy rises to 54.55%. This is 21.22 percentage points above chance assuming that the probability of success by chance is 33.33% across the three verdicts (binomial test: $p < .001$). When relying on a dichotomous measure of accuracy, and merging 'pants-fire', 'false', and 'mostly-false' into false and 'half-true', 'mostly true', and 'true' into true; the accuracy of ChatGPT does not rise compared to chance (68.28% accuracy — which is 18.28 percentage points above chance). We can see on the left panel of Figure 2 that ChatGPT correctly classified 86.9% of the pants-on-fire claims as false, 74.2% of false claims as false, 70.4% of the true claims as true, and 64.8% of the mostly true claims as true.

The binary prompt instructed ChatGPT to classify claims as either true or false. We excluded 1828 claims on which ChatGPT refused to give a verdict (N = 19'324). In Figure 1, we see ChatGPT was more accurate at classifying claims rated as clearly true or clearly false by fact-checkers. For instance, ChatGPT classified 81% of pants-on-fire claims as false and 69% of false claims as false. Similarly, ChatGPT classified 80% of true claims as true and 73% of mostly true claims as true. Overall, when relying on a dichotomous measure of accuracy (merging 'pants-fire', 'false', and 'mostly-false' into false and 'half-true', 'mostly true', and 'true' into true), we found that ChatGPT accurately labeled 68.79% of the claims — which is 18.79 percentage points above chance assuming that the probability of success by chance is 50% across the two verdicts (binomial test: $p < .001$). We can see on the right panel of Figure 2 that ChatGPT correctly classified 80.7% of the pants-on-fire claims as false, 68.6% of false claims as false, 80% of the true claims as true, and 72.7% of the mostly true claims as true.

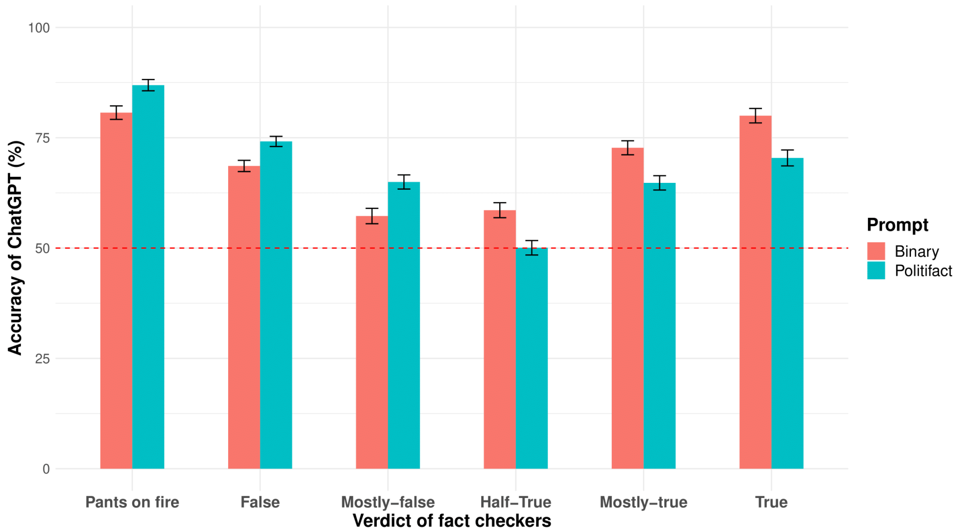

Figure 2: Accuracy of ChatGPT at classifying claims fact-checkers rated as 'pants-fire', 'false', and 'mostly-false' as false, and 'half-true', 'mostly true', and 'true' as true. In red when elying on the prompt using the Politifact labels, and in green when relying on the prompt using only true or false labels. The dotted red lines represent the probability of success by chance.

Next, we investigated the accuracy of ChatGPT over time and as a function of the source of the false claim (e.g., TV/Radio). We did so relying only on the binary prompt using clear true or false labels given the overall similar performance of both explored prompts. We found that ChatGPT did better on statements that have been more recently fact-checked. First of all, ChatGPT was more likely to give a verdict for statements that have more recently been fact-checked (r = .66 [.24, .87], p = .006). The percentage of statements that received a verdict went from 82.7% in 2007 to 93.4% in 2021 (and 92.1% in 2022 (see Figure 4 in the Supplementary Information (SI)). Second, the accuracy of ChatGPT was higher for more recently fact-checked statements (r = .59 [.13, .84], p = .017). The accuracy of ChatGPT went from 61.5% in 2007 to 76.7% accuracy in 2021 (and 73.2% in 2022; see Figure 3).

We then investigated the accuracy of ChatGPT as a function of the source of the false claims. As can be seen in Figure 3, the accuracy of ChatGPT was higher when fact-checked information originated from blogs (77.7% accuracy), emails (73%), or social media (72.9%), compared to the campaign (64%) or testimony (67.2%). Because to date it is unknown what data ChatGPT was trained on, it is unclear why its performance varies per source.

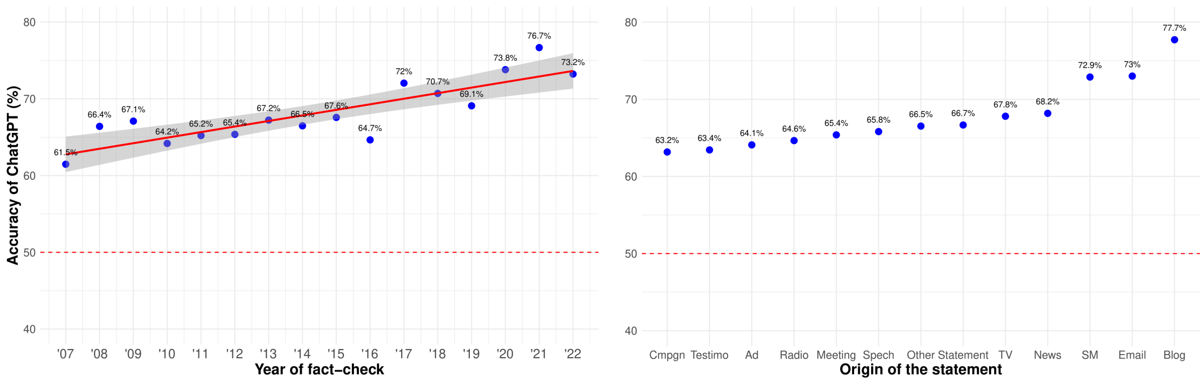

Figure 3: Accuracy of ChatGPT over time (on the left) and as a function of the origin of the fact-checked statement (on the right; N = 19'324). On the left panel, we additionally plotted a regression line with 95% confidence intervals.

Three robustness checks help us to address the issue of memorization. First, we looked at the accuracy of ChatGPT right after and right before its training set (September 2021). We found that the accuracy of ChatGPT was similar 10 months after (75.00% accuracy) compared to 10 months before its training set (75.89%). Note that when looking at overall accuracy throughout time, ChatGPT was much more accurate at classifying statements that have been fact-checked after its training set than between 2007 and the end of 2020 (67.75% accuracy). Second, we looked at the accuracy of ChatGPT on claims related to the ongoing war in Ukraine that started after its training set's cutoff date. We identified these claims with a dictionary and manually filtered out claims that did not relate to the war (see Section 6.3 in the SI for more detail). Out of 94 claims, and after excluding 13 no verdicts, we found that ChatGPT's correctly classified 69.14% of the claims (56/81), which is lower than its general post-training accuracy (75.00%), but similar to its overall accuracy before 2021 (67.75%). Third, we looked at the accuracy of ChatGPT on true claims that have not been fact-checked and that appeared after its training set. Out of 242 claims, and after excluding 54 no verdicts, we found that ChatGPT correctly classified 87.23% of the claims as true (164/188).

We conducted a linear regression (OLS) to investigate the predictors of ChatGPT accuracy (see Table 1 in the SI for the full regression table). We found that accuracy increased over time ($b = .01$, $p < .001$) and that accuracy was higher for statements fact-checkers classified as true compared to false ($b = .04$, $p < .001$), while accuracy was not significantly higher before the training set than after ($b = .02$, $p = .32$). Moreover, accuracy was higher for statement originating from blogs than all other sources except emails ($b = -\ .02$, $p = .42$).

Finally, we offer a first, modest exploration of the accuracy of ChatGPT across topics covered in the fact-checks. Out of 6000 claims that we could reliably assign to a topic (see Section 6.2 in the SI for more detail), and after excluding 468 no verdicts, we found that ChatGPT was more accurate at classifying claims related to COVID-19 (82.10%) compared to all other claims whose accuracy ranged from 63.8% (for government-related claims) to 69.6% (for claims related to policing); see Figure 5 in the SI).

3 Discussion

This study demonstrates the potential of leveraging ChatGPT and other LLMs for enhancing the efficiency and expediency of fact-checking processes. At the very least, our findings underscore the importance of further in-depth inquiries into the content moderation capabilities and properties of LLMs, both in automated and human-mediated contexts. Given the ever-growing role that social media and other digital platforms play in shaping public discourse, it is imperative that we not only enhance our understanding of how LLMs can be abused to harm the quality of our information ecosystem, but also how we can leverage them to promote responsible and ethical content moderation practices.

Although there were instances where ChatGPT failed to classify statements, such cases were relatively infrequent and might be even less frequent using GPT-4, which is also able to process images. The instances where ChatGPT arrived at conclusions contrary to those of human fact-checkers were also relatively rare, but the overall performance of ChatGPT is — although better than chance — still far from 100%. However, a perfect agreement may be an unrealistic threshold, particularly when considering that agreement rates among fact-checkers are themselves not without flaws (Lim, 2018).

Given the nature of LLMs, it is likely that ChatGPT performs better for textual sources and our results indeed show that ChatGPT's accuracy was higher for statements originating from sources such as blogs, email and social media. Regardless, more insight into the training data of ChatGPT is needed to come to a useful assessment of why its performance varies across sources. Moreover, the performance of ChatGPT may also depend on the extent to which it was trained with fact-checking data. Still, addressing this issue, various robustness checks show that ChatGPT's accuracy was similar before and after its training data's cutoff date, and it performed well on claims that have not been fact-checked. We also urge future endeavours into ChatGPT's performance across different topics more in-depth, using other approaches such as a few-shot supervised classifier instead of an unsupervised approach like LDA to separate the claims with a higher precision and particularly a higher recall to cover more of the claims in the dataset.

To conclude, considering the continued prevalence of trustworthy (online) content (Acerbi, Altay, & Mercier, 2022) in contrast to increasing levels of skepticism among the public (Hoes, von Hohenberg, Gessler, Wojcieszak, & Qian, 2022) ChatGPT could be a future tool to increase the labeling of accurate rather than (only) false information. This may be a welcome addition to fact-checking organizations which — due to limited time and resources — increasingly focus on fact-checking false claims, and to social media platforms, which typically focus on flagging harmful content (Alizadeh et al., 2022). In our data (see Figure 6 in the SI), the proportion of statements fact-checked as false (compared to true) increased drastically after 2018 ($r = .85$ [.60, .94]). Before 2019, 46.34% of statements were fact-checked as false by fact-checkers, while after 2018 81.38% of statements were fact-checked as false by fact-checkers, a 35 percentage points increase. By focusing on what is true online rather than solely on what is false, ChatGPT could aid in shifting the balance of online discourse towards accuracy and reliability by accurately identifying and labeling true claims, thereby amplifying their visibility and impact (van der Meer, Hameleers, & Ohme, 2023).

We identify the following questions and steps as promising avenues for future research: (i) performance of ChatGPT across other fact-checking datasets, including those in different countries and languages; (ii) performance of ChatGPT for other content moderation practices, such as identifying hate speech (Huang, Kwak, & An, 2023) and other harmful content; (iii) the performance of ChatGPT beyond short claims across multiple types of (longer) texts (Gilardi, Alizadeh, & Kubli, 2023); (iv) assess the performance of GPT-4 in doing these tasks, (v) assess and compare the performance of ChatGPT or other LLMs and its potential usefulness to fact-checkers and (vi) to Machine Learning models.

Last but not least, it is important to stress that while LLMs such as ChatGPT can potentially help make significant strides in the realm of fact-checking, it is crucial to recognize that it cannot replace the human element of this task (yet). While LLMs may offer speed and consistency, they lack the nuanced understanding and critical thinking skills that are essential for effective fact-checking. Human fact-checking experts bring a depth of experience, context, and judgment that are unlikely to be replicated by any machine. To rely solely on technology for fact-checking could potentially lead to the spread of misinformation and mistrust in the accuracy of information dissemination. Therefore, it is crucial that LLMs are viewed as a supportive tool to augment the work of human experts, rather than a substitute for it.

4 Materials & Methods

4.1 Fact-checking Data

We relied on a database[6] collected from the popular fact-checking website *PolitiFact*. The dataset contains 21,152 statements from 2007 up to including 2022 that are fact-checked by experts into one of six categories: true, mostly true, half true, mostly false, false and pants on fire, the latter of which is PolitiFact's category for statements that are blatantly false. Because PolitFact journalists cannot feasibly check all claims, they select the most newsworthy and significant ones and only check statements that are rooted in facts and are thus verifiable.[7]. In our analysis, we rely on the full dataset.

4.2 ChatGPT Annotation

We relied on the OpenAI Chat API with the 'gpt-3.5-turbo' version to classify the statements. The annotation was conducted between April 16th and May 2nd, 2023. For each annotation task, we prompted ChatGPT with the following annotation instruction text for the PolitiFact prompt:

> Can you fact-check a statement for me? When fact-checking, avoid negations and only use one of the following labels to classify each statement:
>
> - TRUE – The statement is accurate and there's nothing significant missing.
> - MOSTLY TRUE – The statement is accurate but needs clarification or additional information.
> - HALF TRUE – The statement is partially accurate but leaves out important details or takes things out of context.
> - MOSTLY FALSE – The statement contains an element of truth but ignores critical facts that would give a different impression.
> - FALSE – The statement is not accurate.
> - PANTS ON FIRE – The statement is not accurate and makes a ridiculous claim.
> - NO VERDICT – The statement lacks sufficient context, or there is not enough information to assess the veracity of the statement.

We copied these six categories and the definition of each from Politifact's Truth-o-Meter ratings to facilitate a straightforward assessment of ChatGPT's performance against PolitiFact's fact-checkers (our gold standard). In PolitiFact's own words, "the goal of the Truth-O-Meter is to reflect the relative

[6] `https://www.kaggle.com/datasets/rmisra/PolitiFact-fact-check-dataset`
[7] `https://www.PolitiFact.com/article/2018/feb/12/principles-truth-o-meter-PolitiFacts-methodology-i/`

accuracy of a statement. The meter has six ratings, in decreasing level of truthfulnes" (PolitiFact, 2022).

The instruction text for the binary prompt was as follows:

> "Can you fact-check a claim for me? When fact-checking, avoid negations and only use clear language such as 'true', 'false', or 'no verdict'. Use the 'no verdict' label when the claim lacks sufficient context, or there is not enough information to assess the veracity of the claim."

For both prompts, we included the category 'No Verdict' as some claims in PolitiFact's dataset are referring to pictures, videos, or using demonstrative pronouns (e.g., 'these people'), to which ChatGPT has no 'access'. In the vast majority of cases, ChatGPT's output could be easily categorized with regular expressions either into one of the six categories, or into one of two categories. Only in very few instances for the first prompt (0.7% of all 21,152 claims) and relatively few instances for the second prompt (8%) ChatGPT refused to classify a claim (no verdict) because it indeed had insufficient information to classify the statement. Also for both prompts — as it is a text classification task — we set the *temperature* parameter at 0 to focus on the outputs with the highest probability, which makes them more deterministic. This is in opposition to higher temperature values, which make the outputs more varied, and is a setting preferred in text generation — rather than classification — tasks. The instruction texts were repeated every time when prompting ChatGPT with a new claim (classification task).

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6 Supplementary Information

6.1 Additional Analyses

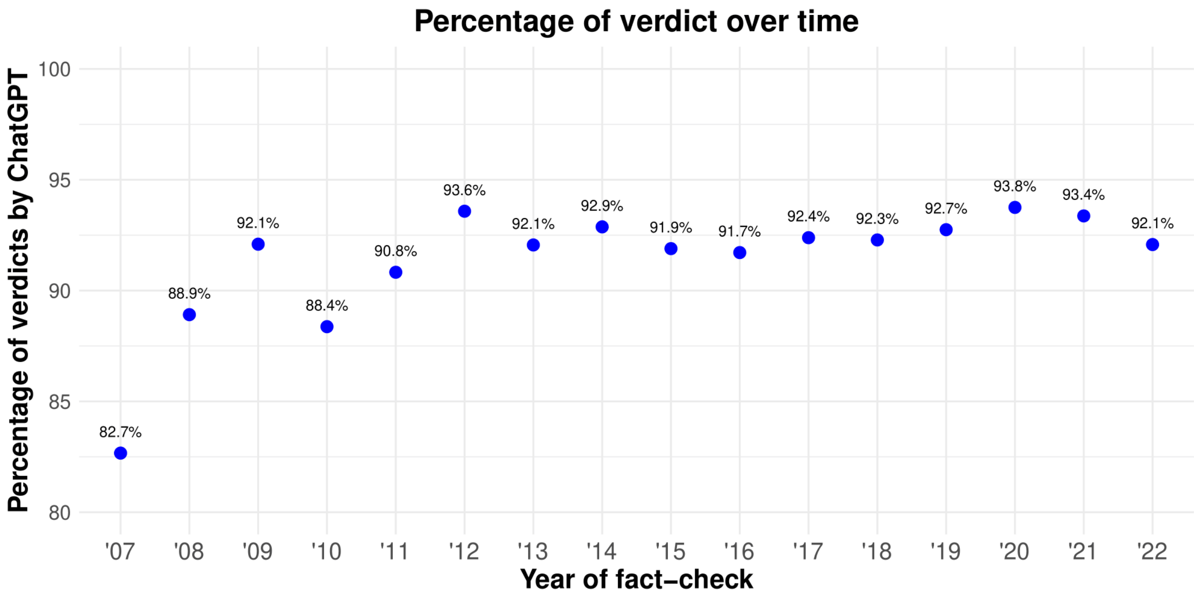

Figure 4: ChatGPT's verdicts (in percentages) over time

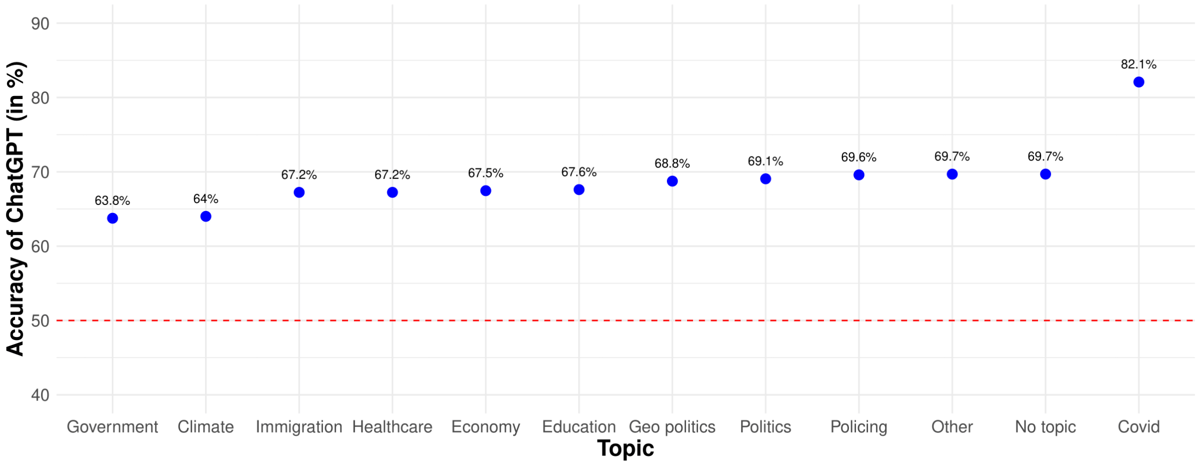

Figure 5: Accuracy of ChatGPT as a function of the topic of the claims (N = 5'542)

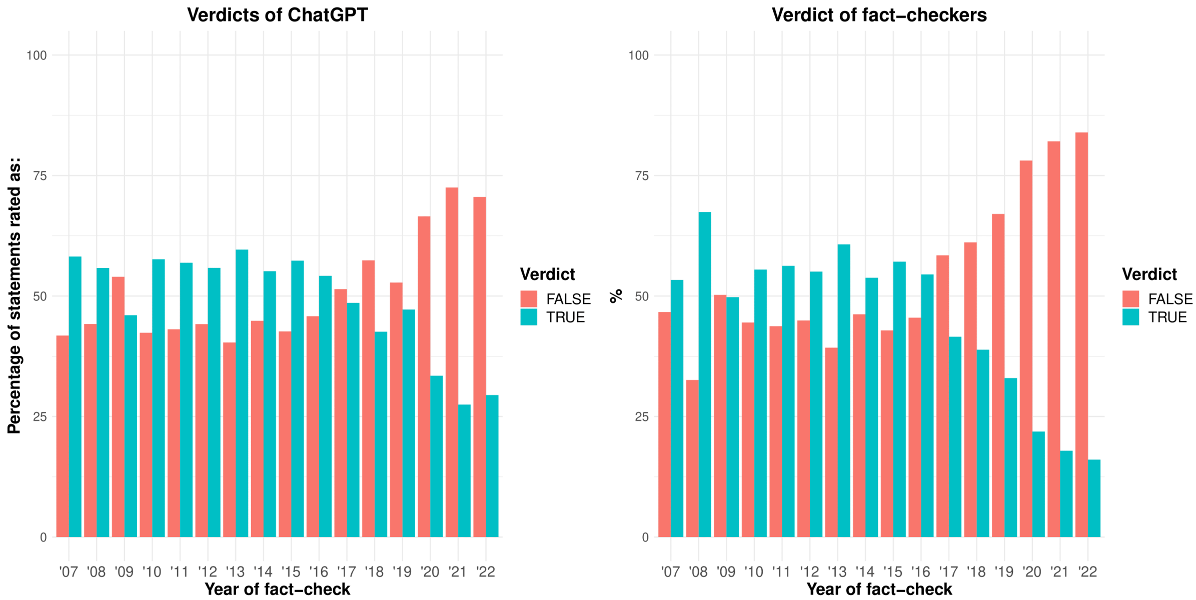

Figure 6: ChatGPT's and fact-checkers' verdicts (in percentages) over time

6.2 Topic Modeling

We grouped the statements into different topics using a weakly supervised or seeded LDA model (Lu, Ott, Cardie, & Tsou, 2011). We first fitted a traditional LDA model to identify topics and relevant terms which we used as the basis for the seed or weak labels shown in Table 2. We chose a higher pseudocount, $C_w = 10\%$, instead of the usual 1%, as some of the topics have very distinctive terms (i.e.: "covid", "obamacare", "taxcut", etc.). After fitting the seeded LDA model, we obtained a word distribution per topic that is consistent with each topic's definition, with the exception of Climate Change, as seen on Table 3. Qualitative evaluation of the top 20 most representative documents per topic also revealed a consistent clustering of documents with the exception, again, of Climate Change.

To evaluate the accuracy of ChatGPT across the different topics, we filtered the top-500 claims per topic in terms of their likelihood to ensure a high precision. Additionally, we sampled 500 statements that were below the top-500 threshold and labeled them as 'no_topic'. The topic 'other' is a residual class that captures related statements that do not belong in any of the seed topics.

6.3 Identifying Statements about the War in Ukraine

We used the regex pattern shown next to identify statements about the War in Ukraine. We then manually removed statements that were not about the war.

putin|ukraine|ukrainian|zelenskyy|russian (invasion|war|conflict|army|forces)

Table 1: OLS Regression Predicting ChatGPT Accuracy

	Model 1
(Intercept)	-12.19 ***
	(2.29)
Year	0.01 ***
	(0.00)
2017-2020 [10 months after training set]	-0.02
	(0.02)
10 months before training set [10 months after training set]	0.02
	(0.02)
True claims [False]	0.04 ***
	(0.01)
Social Media [Blog]	-0.07 ***
	(0.02)
News [Blog]	-0.09 ***
	(0.02)
Email [Blog]	-0.02
	(0.03)
TV [Blog]	-0.10 ***
	(0.02)
Campaign [Blog]	-0.13 ***
	(0.02)
Ads [Blog]	-0.12 ***
	(0.02)
Radio [Blog]	-0.12 ***
	(0.03)
Statement [Blog]	-0.10 ***
	(0.03)
Speech [Blog]	-0.11 ***
	(0.02)
Meeting [Blog]	-0.12 ***
	(0.03)
Other [Blog]	-0.10 ***
	(0.02)
N	19097
R2	0.01

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 2: Seed topics and terms

Topic	Seed Terms
Politics	ad, administration, aoc, barack, beto_orourke, biden, bush, campaign, candidate, congress, congress, congressman, congresswoman, democrat, ...
Government Financing	budget, debt, debt_ceiling, deficit, federal_funding, funding, government_funding, government_spending, national_debt, spending, ...
Economy	boom, economic, economy, economy, employee, fed, federal_reserve, gas_price, gdp, growth, income, inequality, inflation, interest_rate, ...
Healthcare	aca, doctors, health, health_care, health_insurance, healthcare, hospitals, hospitals, insurance, medicaid, medicare, obamacare, social_security, ...
Immigration	asylum_seeker, border, border_control, border_crisis, border_crossing, border_patrol, border_security, border_wall, citizenship, daca, ...
Covid	CDC, astrazeneca, corona, coronavirus, covid, covid19, face_mask, fauci, hydroxychloroquin, lockdown, moderna, mrna, omicron, pandemic, ...
Education	charter_school, college, education, graduation_rate, graduation_rate, private_school, public_school, public_schools, school, school_board, ...
Policing, Gun Control, and Crime	ar15, assault_rifle, assault_weapons, background_checks, crime, gun_control, gun_legislation, gun, illegal_guns, mass_shooting, ...
Geopolitics	afghanistan, attack, bengahzhi, bomb, international_conflict, invasion, iran, iraq, isis, libia, military, national_security, russia, syria, taliban, ...
Climate Change	carbon, climate_change, co2, co2_levels, cop, cop21, emissions, fossil_fuels, global_warming, greenhouse, greta, greta_thunberg, ...

Table 3: Top-10 representative terms per topic

Topic	Top-10 terms
Politics	administration, biden, campaign, candidate, congress, democrat, democrats, election, house, joe_biden
Government Financing	budget, cut, debt, deficit, federal, funding, governor, increase, pay, percent
Economy	create, economic, economy, employee, gas_price, gdp, growth, income, inflation, job
Healthcare	americans, benefit, cost, federal, government, health, health_care, health_insurance, healthcare, insurance
Immigration	america, border, border_patrol, citizenship, country, history, ice, illegal_alien, illegal_immigrant, illegal_immigration
Covid	case, cause, cdc, child, coronavirus, covid, covid_vaccine, death, die, drug
Education	city, college, county, education, florida, graduation_rate, high, nation, percent, public
Policing, Gun Control, and Crime	america, arrest, black, child, crime, gun, kill, man, murder, nra
Geopolitics	afghanistan, american, attack, bomb, donald_trump, hillary_clinton, hold, iran, iraq, isis
Climate Change	big, car, climate_change, company, cop, dollar, energy, federal, fund, gas
Other (Residual Topic)	abortion, act, allow, ban, change, florida, gov, governor, issue, law